The Role of Public Clinics in Preventable Hospitalizations Among Vulnerable Populations

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Objective. To determine if the availability of public ambulatory clinics affects preventable hospitalization (PH) rates of low-income and elderly populations.
Data Sources. PH rates were calculated using elderly and low-income discharges from 1995–97 Virginia hospital discharge data. Other data sources include the 1990 Census, the 1998 Area Resource File, the 1996 American Hospital Association Survey, the Virginia Department of Health, the Virginia Primary Care Association, and the Bureau of Primary Health Care.
Study Design. Multiple linear regression was used to evaluate the relationship between ambulatory clinic availability and PH rates, controlling for population and other provider characteristics in a cross-section of zip code clusters.
Data Extraction Methods. Clusters with populations of at least 2,000 were assembled from zip codes in each county in the state of Virginia. Overlapping medical market service areas were constructed around the population centroid of each cluster.
Principal Findings. Populations in medically underserved areas (MUAs) served by a Federally Qualified Health Center had significantly lower PH rates than did other MUA populations. The presence of a free clinic had a marginally significant association with lower PH rates.
Conclusions. The availability of public ambulatory clinics is associated with better access to primary care among low-income and elderly populations.
Key Words. Preventable hospitalizations, ambulatory clinics, access to care

Variation in rates of preventable hospitalizations (PHs)—hospitalizations for conditions that, if treated properly on an outpatient basis, would usually not require inpatient admission—may indicate inequities in access to primary care services. These effects are likely greatest among populations facing financial and geographic barriers to care. Prior research has explored associations primarily between PH rates and demographic and socioeconomic factors in the general population. However, especially among vulnerable populations, little is known about the correlation between PH rates and factors that public policy can affect.

BACKGROUND

Prior Research

The first studies of PHs evaluated relationships between population characteristics and PH rates among nonelderly persons. Poverty rates consistently have been shown to be associated directly with PH rates. Other correlates of PH rates include education level, race, age, and gender. Populations that are less educated and contain proportionately more minority, elderly, and female persons exhibit higher PH rates (Begley et al. 1994; Billings, Anderson, and Newman 1996; Billings, Zeitel, Lukomnik, et al. 1993; Pappas et al. 1997). Uninsured and Medicaid patients have been found to have higher PH rates than insured patients (Weissman, Gatsonis, and Epstein 1992). Bindman, Grumbach, Osmond, et al. (1995) provide solid evidence linking PH rates to perceived limits on access to care. On this basis, PH rates have been studied as an indicator of access to care.

Research on medical provider characteristics and PH rates remains limited and less conclusive. Three studies focused on the relationship between physician supply and PH rates. Parchman and Culler (1994) found a significant inverse correlation between PH rates and the supply of family and general practice physicians, but they did not adjust for other intervening factors. After adjusting for some population characteristics, Krakauer et al. (1996) failed to find a significant relationship between PH rates for Medicare beneficiaries and generalist physician supply. Schreiber and Zielinski (1997) also adjusted for population characteristics, however, and found a direct correlation between primary care physician supply and PH rates. Although proximity to hospitals has been established as a prominent determinant of hospital utilization patterns (Cohen and Lee 1985; Dranove, White, and Wu 1993), the study by Schreiber and Zielinski (1997) is the only one of PH rates to include this factor. They found a direct association between hospital proximity and PH rates in rural areas.

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CONCEPTUAL FRAMEWORK: AN ECONOMIC MODEL OF AMBULATORY CARE

Individuals with ambulatory care–sensitive (ACS) conditions (i.e., conditions for which hospitalizations are considered preventable) may seek primary care from a range of providers: a primary care physician's office, an ambulatory clinic, or a hospital emergency room. Their choices of setting and amount of care depend on the relative costs and benefits of each option, their personal preference sets, and their abilities to pay.

Vulnerable populations by definition have relatively limited access to care. For example, they may lack health insurance and therefore face higher out-of-pocket prices than those with insurance for the same medical services. Alternatively, they may suffer from impaired mobility and therefore face higher inconvenience costs than unimpaired persons for physical access to medical care. Similarly, persons residing in underserved areas have fewer options for primary care than do others. For both vulnerable populations and residents of underserved areas, the range of available primary care provider options may be more limited, and the relative price of obtaining primary care may be higher. Thus, their propensity to forgo needed primary care is likely to be higher than for other populations. If adequate primary care is not obtained, a PH may result.

The PH rate is expected to depend on a number of factors. One set includes the socioeconomic and demographic characteristics of the population, such as age, gender, race, ACS condition prevalence, and insurance status. Another set incorporates the availability and relative effective prices of primary care providers. All else being equal, more primary care providers serving a vulnerable population should help reduce the PH rate by making it easier and less expensive to obtain care. The availability and relative price of alternatives to primary care (namely hospitals) comprises a third set of factors. Hospital characteristics such as proximity, capacity, and input price levels are related to a hospital's ability to function as a substitute source of primary care. Patients can obtain care from nearby hospitals more easily than from distant hospitals. Areas with more beds relative to population or lower hospital input costs may experience lower prices for hospital services or a greater willingness by hospitals to provide free care. Populations with attractive (i.e., less expensive, closer) substitutes are likely to have higher PH rates.

This study investigated the associations between characteristics of medical providers, including hospitals, physicians, and public ambulatory clinics, and PH rates among low-income and elderly persons. Inadequate data have precluded prior analysis of these issues. For this reason, a new database was constructed combining Virginia hospital discharge data with population and medical provider characteristics from a variety of sources. The units of analysis are small geographic areas consisting of clustered zip codes and flexible, overlapping medical market definitions.

EMPIRICAL METHODS

All Virginia zip codes were grouped into clusters of at least 2,000 population. Relevant market areas were determined for each cluster for each of the three provider types (physicians, hospitals, and ambulatory clinics). Finally, the dependent variable, low-income and elderly PHs per 1,000 total population, and explanatory variables were calculated at the cluster level. The final analytic sample contained 435 clusters.

Constructing Zip Code Clusters

The constructed database of zip code–level and county-level characteristics for the state of Virginia was built with data from the 1995–97 Virginia hospital discharge files, the 1998 Area Resource File (which includes county-level demographic and physician supply data from prior years), the 1996 American Hospital Association Annual Survey of Hospitals, and the 1990 Census zip code–level file STF3B. Creating the database involved steps to identify the appropriate geographic areas and to combine the zip codes into clusters of at least 2,000 population.[1]

Flexible, overlapping market areas offer a more accurate picture of health service options than do counties or Health Care Service Areas (HCSAs) (Morrisey 1993). Using counties as proxies for market areas introduces boundary bias; residents are assumed to use only the resources in their county even if closer options exist in a neighboring county. HCSAs were designed to represent self-contained service areas; consequently, they are large, often consisting of multiple counties, and overly inclusive.

Each cluster was assigned a geographic market area for each of the three types of medical providers (physicians, hospitals, and clinics). For convenience in using county-level physician data from the Area Resource File, the market area for primary care physician services was defined as the county in which a cluster was located. The market area for hospital services was defined as the set of zip codes (not zip code clusters) falling within a 15-mile radius of the population centroid (the population-weighted geographic center) of the cluster.

The definition of the market area for ambulatory clinic services was similar to the hospital market area definition. It was further refined to reflect the theoretical assumption that the decision to visit an ambulatory clinic depends in part on the availability of substitutes, particularly hospitals. In the absence of data on clinic market areas, a conservative expectation is that if patients would visit clinics at all, they would visit clinics that were closer than the closest hospital. Thus, the radius used for each cluster's clinic market area varied and was a function of the proximity of the nearest hospital. In cases where the nearest acute care hospital was at least 15 miles away, the radius was 15; when the nearest hospital was no more than five miles away, the radius was five. Otherwise the length of the radius was the distance to the nearest hospital (between 5 and 15 miles). Alternative market definitions using fixed 10- and 15-mile radii were also tested.

Calculating PH Rates

Table 1 shows all ACS conditions, the associated ICD-9 codes, and their relative frequencies. The list of ACS conditions used was developed from the intersection of the lists in Weissman, Gatsonis, and Epstein (1992), Billings, Zeitel, Lukomnik, et al. (1993), and Millman (1993), as done by Culler, Parchman, and Przybylski (1998). The following conditions were included: angina, asthma, cellulitis, chronic obstructive pulmonary disease, congestive heart failure, dehydration, diabetes, gastroenteritis, grand mal seizures and epileptic convulsions, hypertension, hypoglycemia, kidney and urinary tract infections, pneumonia, and severe ear, nose, and throat infections.

Aggregate zip code cluster–level PH rates were calculated by summing hospital discharges from January 1995 through December 1997 indicating any primary ICD-9 diagnosis code previously identified as an ACS condition. Because ambulatory clinics serving vulnerable groups were a major focus of this analysis, only ACS discharges with payment source indicated as Medicare, Medicaid, charity/indigent, self-pay, or government were counted; patients with private insurance coverage were excluded from this analysis. In addition, patients who transferred in from another health care facility were excluded because of uncertainty about the "preventability" of their hospitalizations. Overall, there were 254,234 PHs in Virginia during 1995–97, 66 percent of which involved low-income or elderly individuals. The

Table 1: Roster of ACS Conditions, Related ICD-9-CM Codes, and Share of PHs Among Low-Income and Elderly Discharges and Among All Discharges in Virginia, 1995–97

		Proportion of PHs in Virginia, 1995–97	
ACS Condition	*ICD-9-CM Codes*	*Low-Income and Elderly Discharges*	*All Discharges*
Angina	411.1, 411.8, or 413	3.4%	4.0%
Asthma	493, 493.0, 493.01, 493.1, 493.2, or 493.9	0.1%	0.4%
Cellulitis	263, 264, 681, 682, 682.0–682.9, 683, or 686	4.8%	5.9%
Chronic obstructive pulmonary disease	466, 491, 491.1, 491.20, 491.21, 491.8, 492, 492.0, 492.8, 494, or 496	14.3%	13.6%
Congestive heart failure	402.01, 402.11, 402.91, 428, 428.0, 428.1, 428.9, or 518.4	28.7%	24.2%
Dehydration	276.5	10.5%	10.7%
Diabetes	250.0–250.3, 250.8–250.10, 250.12, 250.13, 250.20, 250.22, 250.23, 250.30, 250.32, 250.33, 250.90, 250.92, or 250.93	1.7%	2.3%
Gastroenteritis	558.9	3.2%	4.4%
Grand mal seizures and epileptic convulsions	345.0–345.9, or 780.3	3.6%	4.5%
Hypertension	401.0, 401.9, 402.00, 402.10, or 402.90	1.3%	1.6%
Hypoglycemia	251.2	0.2%	0.2%
Kidney/urinary tract infections	590, 590.2, 590.9, 590.10, 590.11, 599.0, or 599.9	8.1%	7.9%
Pneumonia	481, 482.2, 482.3, 482.9, 483, 483.0, 485, or 486	19.4%	19.6%
Severe ear, nose, throat infections	382, 382.1–382.9, 382.00–382.02, 462, 463, 464, 465, or 472.1	0.6%	0.8%
Total number of preventable hospitalizations		168,326	254,234

Source: ICD-9-CM, International Classification of Diseases, 9th Revision, Clinical Modification.
Note: Low-income and elderly discharges are defined by payer source equal to one of the following: Medicare (over 65 years old only), Medicaid, Self-Pay, Indigent/Charity, or Government.

denominator for the PH rate was total estimated 1996 cluster population, based on county-level Census growth rates from 1990.[2]

Because of high variability in the PH rate (due in part to discrepancies between hospital discharge and zip code population data), the population of 485 clusters was trimmed by 10 percent to exclude those clusters in the top or bottom 5 percent of the distribution of total inpatient discharges per capita.[3]

The remaining 435 clusters in the analytic sample represent 88.4 percent of the total Virginia population and 90.6 percent of low-income and elderly PHs statewide.

Model Specification

Descriptive statistics for the model variables in the analytic sample are shown in Table 2. To control for age and gender, the model contained a vector of variables describing the percentage distribution by age and gender: 0–18, 19–34, 35–49, 50–64, 65–74, and 75 and over. The omitted group was males 19–34. Also controlled for were the proportion of the cluster population that was Hispanic or non-white (i.e., 1 minus the proportion of the population that was non-Hispanic white), the proportion of cluster households with 1989 total annual income no higher than $15,000, and the proportion of the cluster population at least 25 years old with at least some college education.

Provider characteristics in this analysis included the availability of hospitals, physicians, and public ambulatory clinics, as well as hospital input prices. Both distance to the nearest acute care hospital and acute care hospital beds per capita (calculated as the sum of beds in a 15-mile radius from the cluster population centroid divided by the sum of zip code populations in the same 15 miles) were included. Per capita primary care physician supply (calculated as the sum of general practice and family practice physicians per 1,000 population) was included at the county level from the Area Resource File. The average salary per hospital full-time equivalent (FTE) employee (calculated based on hospitals in a 15-mile radius or on the closest hospital for clusters not served by a hospital within 15 miles) served as a proxy for hospital input price.

The relationship between proximity of ambulatory clinics and PH rate was measured using two types of clinics: Federally Qualified Health Centers (FQHCs) and free clinics. The model included two dummy variables that indicated whether a cluster's market area for ambulatory clinic services included at least one FQHC or one free clinic, respectively. FQHCs are not-for-profit community-based care practices located in underserved areas that provide services to Medicare, Medicaid, and uninsured patients. They are funded primarily through project grants and cost-based reimbursement for services provided under Medicaid and Medicare. Free clinics are locally run, privately funded clinics usually located in urban areas that provide free

Table 2: Definition, Mean, and Standard Deviation of Model Variables

Variable	*Definition*†	*Mean*	*S.D.*
Dependent variable			
PH rate	Three year (1995–97) low-income and elderly PHs per 1,000 total population. Includes only discharges where payer type equals Medicare (over 65 only), Medicaid, self-pay, indigent, charity, or government; excludes discharges where source of admission equals transfer	27.418	16.267
Independent variables			
Age and gender distribution‡			
Male 0–18	Proportion of population male 0–18	0.132	0.023
Male 35–49	Proportion of population male 35–49	0.110	0.020
Male 50–64	Proportion of population male 50–64	0.068	0.016
Male 65–74	Proportion of population male 65–74	0.033	0.013
Male 75+	Proportion of population male 75+	0.017	0.009
Female 0–18	Proportion of population female 0–18	0.124	0.021
Female 19–34	Proportion of population female 19–34	0.129	0.029
Female 35–49	Proportion of population female 35–49	0.110	0.020
Female 50–64	Proportion of population female 50–64	0.073	0.017
Female 65–74	Proportion of population female 65–74	0.041	0.016
Female 75+	Proportion of population female 75+	0.032	0.017
Socioeconomic characteristics			
Income < $15K	Proportion of households with 1989 income less than $15,000	0.236	0.126
Minority	Proportion of population non-white or Hispanic	0.218	0.188
College	Proportion of population aged 25+ with some college	0.404	0.185
Hospital and physician characteristics			
Beds per capita	Acute care hospital beds per 1,000 population; market area equals 15-mile radius around cluster population centroid	2.392	2.055
Distance to hospital	Distance in miles to closest acute care hospital	9.593	7.790
Hospital salary	Average hospital salary per FTE in thousands of dollars; based on all hospitals in 15-mile radius around cluster population centroid or closest hospital (for clusters with no hospitals in radius)	32.449	7.126
GP/FPs per capita	General and family practitioners per 1,000 population; market area is county in which cluster is located	0.540	0.275

Ambulatory clinic supply§			
FQHC	Dummy: equals 1 if there is at least one FQHC in market	0.200	0.400
FC	Dummy: equals 1 if there is at least one free clinic in market	0.290	0.454
MUA	Dummy: equals 1 if cluster is located in partial or full county federal MUA	0.623	0.485
FQHC and MUA	Dummy: equals 1 if there is at least one FQHC in market AND cluster is located in partial or full county MUA	0.172	0.378

Note: $N = 435$ clusters.

†All variables are defined at the zip code cluster level unless otherwise specified.

‡Reference group is males 19–34.

§The radius for the clinic market area varies by cluster depending on distance to closest acute care hospital and ranges from 5 to 15 miles. See text for details.

services to qualified low-income recipients. Data on the locations of clinics came from the Virginia Department of Health, the Virginia Primary Care Association, and the federal Bureau of Primary Health Care.

FQHCs are located exclusively in federally designated medically underserved areas (MUAs). The MUA designation is determined by the Bureau of Primary Health Care based on an area's poverty rate, proportion of population that is elderly, five-year infant mortality rate, and physician-to-population ratio. A MUA can cover part or all of a county. Because subcounty MUAs were not necessarily coterminous with zip code boundaries, a dummy variable was included identifying clusters located in counties that were whole or partial MUAs. Due to the nature of the market definition, it is possible that a FQHC located in a nearby MUA county could appear in the clinic market area of a cluster located in a non-MUA county. More importantly, people can cross MUA boundaries to obtain care. To isolate the effects of FQHCs on their targeted populations, the model contained an interaction dummy variable that identified clusters served by a FQHC and located in counties that contained or were MUAs.[4]

Model Estimation

The model was estimated by ordinary least squares regression. The model residuals indicated that the amount of variation in the PH rate was related inversely with cluster population. To remove the effects of this heteroskedasticity, Eicker-White robust standard errors were calculated.

Table 3: Linear Regression Model Coefficients, Robust Standard Errors, *p*-Values, and Elasticities

Variable	*Coefficient*	*Robust Std. Error*†	p-*Value*	*Elasticity*‡
Age and gender distribution				
Male 0–18	34.574	47.807	.470	1.663
Male 35–49	111.843	58.602	.057	4.478
Male 50–64	−81.856	89.279	.360	−2.040
Male 65–74	−129.829	116.119	.264	−1.581
Male 75+	−70.835	152.171	.642	−0.446
Female 0–18	43.409	42.729	.310	1.967
Female 19–34	15.737	35.433	.657	0.741
Female 35–49	−37.368	42.801	.383	−1.504
Female 50–64	242.244*	93.830	.010	6.415
Female 65–74	150.580	96.472	.119	2.270
Female 75+	177.434*	74.192	.017	2.060
Socioeconomic characteristics				
Income < $15K	53.806*	13.181	.000	4.622
Minority	2.593	4.392	.555	0.206
College	−12.331*	5.739	.032	−1.819
Hospital and physician supply				
Beds per capita	0.495	0.470	.293	0.432
Distance to hospital	−0.254*	0.120	.034	−0.888
Hospital salary	−0.194	0.099	.051	−2.292
GP/FPs per capita	0.194	2.553	.939	0.038
Ambulatory clinic supply				
FQHC	3.443	2.162	.112	0.251
FC	−2.306	1.250	.066	−0.259
MUA	−0.519	1.280	.685	−0.118
FQHC and MUA	−5.814*	2.652	.029	−0.366
Constant	−10.514	18.386		

*Coefficient is significant at the $p < .05$ level.

†Robust standard errors are calculated using Eicker-White correction.

‡Elasticity indicates the percentage change in the dependent variable associated with a 10 percent increase in the independent variable from its mean.

RESULTS

Table 3 presents the coefficients, robust standard errors, *p*-values, and elasticities from the regression model. The elasticities represent the percentage change in the mean publicly insured PH rate resulting from a 10 percent increase in the mean of each independent variable. The model as a whole is significant and explains better than half the variation in the dependent variable (R^2 = 51.7 percent). Results in general were not sensitive to the definition of clinic market area.

The major finding of this research is that the availability of ambulatory clinics is associated with lower publicly insured PH rates. Clusters in federally designated MUAs that were served by a FQHC had on average 5.8 fewer PHs per 1,000 population over the three years than did clusters in MUAs that were not served by a FQHC ($p = .029$). Clusters served by a free clinic had on average 2.3 fewer PHs per 1,000 population ($p = .066$) than those not served. In addition, vulnerable populations in clusters closer to hospitals and in areas with lower hospital salaries were more likely to be hospitalized for ACS conditions. Distance to the nearest acute care hospital was inversely correlated with publicly insured PH rate ($p = .034$). Higher hospital input prices, as measured by average salary per FTE, were related to lower publicly insured PH rates ($p = .051$).

The socioeconomic and demographic control variables helped explain variation in publicly insured PH rates. Clusters with large proportions of older women had significantly higher PH rates. A 10 percent increase in the proportion of women age 50 and over was associated with about a 10 percent increase in the PH rate. Greater proportions of households with 1989 income less than $15,000 were associated with significantly higher PH rates ($p < .001$), while greater proportions of individuals age 25 and over with some college education were associated with significantly lower PH rates ($p = .032$).

DISCUSSION

This analysis is a first effort in showing that public ambulatory clinics appear to improve access to primary care for vulnerable groups, particularly in underserved areas, and, as a result, lower the rate of PH. The two types of clinics studied in this analysis, FQHCs and free clinics, exist specifically to provide primary and preventive care to vulnerable populations at subsidized prices. All else being equal, vulnerable populations served by a larger and less expensive set of primary care providers have lower PH rates. Because public ambulatory clinics are located commonly in areas with lower access, however, there may be a direct correlation between public clinic availability and publicly insured PH rates.

As Blustein, Hanson, and Shea (1998) point out, the usefulness of the PH rate as an access measure is contingent on adjusting for population characteristics. A naïve analysis of the effectiveness of FQHCs in addressing the primary care needs of their target populations yields a spurious conclusion. About 55 percent (4.2 million) of Virginians resided in a county that was at least a partial MUA. Only about 20 percent of this population was served by a FQHC. However, the unadjusted publicly insured PH rate for this 20 percent was about six PHs per 1,000 population higher than for the 80 percent not served by a FQHC. In fact, after adjusting for population and provider characteristics, this study found that the availability of a FQHC was associated with publicly insured PH rates almost six PHs per 1,000 fewer for populations in MUAs. This is a sizable difference given that the mean three-year cluster-level PH rate in this study is about 27 PHs per 1,000 population. The same analysis of the effectiveness of free clinics yields similar results.

The findings have substantial relevance for public policy. FQHCs have been able to provide services to the medically indigent through subsidies provided by the cost-based reimbursement system for Medicaid and Medicare patients. FQHCs are especially reliant on reimbursement from Medicaid (Nadel 1995). A growing proportion of Medicaid beneficiaries have been switched into managed care programs. According to statistics published on the Health Care Financing Administration web site (http://www.hcfa.gov/medicaid/mcsten97.htm), almost 60 percent of the half-million Medicaid enrollees in Virginia were enrolled in managed care plans as of June 30, 1997. In addition, the Balanced Budget Act of 1997 scheduled cost-based reimbursement for FQHCs to end in 2003. FQHCs can expect their revenues to be diminished in terms of both the amounts they are reimbursed per visit and the number of visits eligible for full reimbursement. These changes could result in diminished access to clinic services for the medically indigent by restricting clinics' ability to shift costs. Further reductions in access to services for uninsured persons would likely increase their PH rates and strain other parts of the safety net.

The availability of acute care hospitals also influenced publicly insured PH rates. Vulnerable populations served by closer and cheaper hospitals have higher PH rates. One possible explanation is that persons with ACS conditions seeking care at hospitals are more likely to forgo primary care until hospitalization is medically necessary. In the study sample, 68 percent of publicly insured PHs were admitted through the emergency room, underscoring the fact that hospitals provide mostly inpatient services. However, overall use of care may be higher in areas with hospitals. It could be that, despite receiving similar amounts of primary care, persons with ACS conditions in these areas may be more likely to be admitted for inpatient care. Without a measure of ambulatory care utilization, this study is not capable of answering this question.

That the more general measure of primary care physician supply was not statistically significant is not worrisome. The role of physician supply on PH rates is not agreed upon in the literature. Moreover, physician supply, which was measured at the county level in this study, is correlated with the presence of hospitals and clinics, even more so in underserved areas. Total primary care physician supply also may not measure accurately the number of physicians serving low-income and elderly persons.

Because the analysis employs some novel methodological features, it is important to reiterate their justification. Limiting the analysis to PHs only among low-income and elderly populations was done because these are populations targeted primarily by public ambulatory clinics. Moreover, because these populations suffer decreased access to primary care, PH rates among these populations deserve attention from policymakers and may respond better to policy interventions.

Although the combination of small areas and flexible markets may not afford the precision of an individual-level analysis of consumer characteristics, this methodology is better suited to detect the influence on the PH rate by provider characteristics, the focus of this analysis. The use of clusters has important ramifications for study findings. Repeated sampling over three years allowed smaller clusters and hence a larger sample size and more precision than would single-year sampling. As a result, small area variation in population characteristics and service availability that would be masked by using larger areas was preserved.

Because this study examines publicly insured PH rates and population characteristics in small geographic areas, the results are vulnerable to the ecological fallacy. The population using ambulatory clinics, for example, may not overlap with the population experiencing ACS conditions. Thus, it is possible that ambulatory clinics may not have an effect in lowering publicly insured PH rates. Two studies have replicated the associations at the individual level between PH rates and income, education, and health status among elderly Medicare beneficiaries (Blustein, Hanson, and Shea 1998; Culler, Parchman, and Przybylski 1998). The data needed to study the effects of provider availability on PHs at the individual level were not available.

The data used in this analysis have other limitations. First, a heterogeneous set of data sources was used. In particular, the cluster population characteristics were derived from 1990 Census data, while publicly insured

PH rates were calculated from discharge data and population estimates for 1995–97. Also, the dependent variable is a crude PH rate that divides low-income and elderly PHs by the total population, not the low-income and elderly population. The cluster population characteristics likewise represent the total population. Second, the study relies on hospital discharge data, which are limited by their administrative nature. Using these data, for instance, one cannot determine whether a given hospitalization is truly preventable. Data from Veterans' Administration hospitals are not included in Virginia discharge data. Furthermore, PH rates in Northern Virginia are likely understated because of the availability of inpatient services in Maryland and the District of Columbia. Finally, the ability to generalize the results of the study, which covers only the state of Virginia, is uncertain. The best way to address these limitations would be to use primary data collected at the individual level.

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NOTES

1. The first step in the database creation process was identifying the geographic areas—zip codes and counties—located in Virginia. A database of all postal zip codes in 1995 was used to develop a list of 1,259 unique Virginia zip codes. The list was matched against the 816 residential zip codes identified in the Census file. Those zip codes from the postal database that could not be matched with the Census file were assigned to the closest (determined by straight-line distance between population centroids) Census zip code.

   Virginia contains a large number of small independent cities. For analytic purposes, the Area Resource File joins the data for each of these cities with those of a neighboring county, yielding a total of 102 county-level entities. This analysis uses these entities, which are identified by a Modified FIPS code. Zip codes crossing county boundaries were assigned to the county in which the majority of their populations resided.

   To ensure a meaningful denominator for the PH rate calculation, the 816 Census zip codes were combined into 485 clusters. The clustering algorithm joined zip codes with fewer than 2,000 people (as determined by the 1990 Census population, adjusted for 1990 to 1996 overall county population growth rates from the Area Resource File) with the closest zip code or zip code cluster in the same county such that the combined population of the joined zip codes had at least 2,000 population. To ensure a maximal number of clusters, zip codes within a county were processed in ascending order of population size. During the cluster-building process, the coordinates of the cluster population centroids were adjusted to compensate for the relative distances and populations of the component zip codes.

2. The proper denominator is low-income and elderly population. However, population counts and characteristics were unavailable for this group. Using total population has two side effects. First, it underestimates the low-income and elderly PH rate. Second, it introduces an additional source of correlation between the socioeconomic and demographic control variables and the dependent variable. The coefficients on these variables will reflect the positive effects of these variables on (1) the probability that individuals will be hospitalized for a preventable condition, and (2) the probability that people who experience PHs will be included in the PH rate because they are covered by Medicare, Medicaid, or other public insurance.
3. To help reduce error from discharge record inaccuracy, county-level aggregates of ACS discharges that were indicated to be from zip codes not present in the postal zip code database were assigned to extant clusters in the same county proportional with cluster population. This involved 1.8 percent of all ACS discharges. This is possible because Virginia hospital discharge records contain separate county and zip code identifiers.
4. Of the 435 clusters in the analytic sample, 164 are not in MUA counties and 271 (62.3 percent) are. Of the 164 non-MUA clusters, 12 (7.3 percent) have FQHCs located within the market radius. Of the 271 clusters in MUAs, 96 (35.4 percent) are served by FQHCs under the flexible clinic market definition. Under a fixed 15-mile market definition for clinics, 118 (43.5 percent) of the 271 clusters are served by FQHCs.

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